



Climate change impacts on socioeconomic activities through labor productivity changes considering interactions between socioeconomic and climate systems

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ARTICLE INFO

Article history:

Received 5 September 2018

Received in revised form

26 November 2018

Accepted 12 December 2018

Available online 14 December 2018

Keywords:

Climate change

Economic activities

Gross domestic product

Energy supply

Labor productivity

Model interactions

ABSTRACT

While human socioeconomic activity leads to climate change, the latter also affects the former; socioeconomic and climate systems have considerable interactions. Some studies have looked at the effects of climate change on labor productivity and gross domestic product, yet they have not considered the interaction between socioeconomic and climate systems. This study therefore examined that aspect as well as the economic impact of climate-change-induced labor productivity change. Business-as-usual and two emissions reduction scenarios—2°C and Representative Concentration Pathway 4.5—were adopted. Data analysis employed a computable general equilibrium model and a simple climate model. The results show that global economic impacts of climate-change-induced labor productivity change have not been large. A negative effect on economic activities was found when the relationship between climate change and labor productivity was considered in the economic model. Although such impacts were larger in the business-as-usual scenario, that was not the case in the 2°C scenario. The results suggest that greater levels of climate change are in accordance with greater socioeconomic impact at the global level. In particular, impact on high-temperature regions was found to be considerable. Interestingly, not all regions experienced economic loss from climate change. Some in the low- to medium-temperature zones received a positive economic effect because of comparative advantage caused by differences in labor productivity changes among regions. The coupled modeling scheme ultimately was effective in evaluating the interaction. Expanded assessment of climate change, mitigation, and adaptation will aid further understanding of the interaction of climate change and socioeconomic activities.

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1. Introduction

1.1. Background and purpose

Climate change studies and policy both emphasize the obvious importance of climate change mitigation in reducing the associated impacts. Such impacts, however, will still remain even if mitigation can be successfully achieved (Intergovernmental Panel on Climate Change, 2014). Understanding of the influence of both mitigation and impacts is therefore vital.¹

Human socioeconomic activities, particularly energy (fossil fuel) use, lead to climate change, and affect the natural environment. These outcomes then influence the socioeconomic system in

various directions through the feedback effects between the natural environment and socioeconomic system. Such feedback effects include decreases in land area because of rising sea levels (Intergovernmental Panel on Climate Change, 2014; Roson and van der Mensbrugghe, 2012; Tol, 2002), changes in agricultural productivity due to changing climate (Boonwichai et al., 2018; Cline, 2008; Roson and van der Mensbrugghe, 2012; Tol, 2002), declining labor productivity caused by heat-induced stress (Kjellstrom et al., 2009a, 2009b; Roson and van der Mensbrugghe, 2012; Tawatsupa et al., 2013), influence of climate change on human health (Béguin et al., 2011; Bosello et al., 2006; Leal Filho et al., 2018; Tol, 2002), and the influence of temperature changes on tourism (Hamilton et al., 2005; Roson and van der Mensbrugghe, 2012). This illustrates the considerable interactions occurring between the socioeconomic and climate systems. More precisely put, if climate change affects socioeconomic conditions, such as through the abovementioned relationships, greenhouse gas (GHG)

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¹ Adaptation to climate change is also important, but is outside the scope of this study.

emissions from human activity are also affected. The degree of climate change is resultantly also affected. Modeling a component of a climate change impact in an economic model can show that the degree of climate change will differ from the level initially assumed (i.e., when climate change impacts are not considered).

Declining labor productivity is a considerable issue among climate change impacts on the socioeconomic system. Heat stress caused by hot weather affects economic activities, leading to economic loss via loss of production (Kjellstrom et al., 2009b). This necessitates evaluation of how climate-change-induced labor productivity change affects socioeconomic activities. As shown in the literature review in the next section, a number of studies have evaluated the relationship between climate change and economic loss via decline in labor productivity. These studies, however, do not consider the interaction between socioeconomic and climate systems (i.e., they only consider unidirectional impacts from the climate system to the human system), although recent studies indicate such interaction is an important consideration in climate change research (Collins et al., 2015; Mercure et al., 2018; Monier et al., 2018; Paltsev et al., 2015; Thornton et al., 2017). The present study therefore addresses this vital interaction in analyzing the impact of climate change through labor productivity change.

The study aims to evaluate the impact of climate change on socioeconomic activities, not only in terms of gross domestic product (GDP) loss, but also in areas such as energy supply. It does so by using modeling approaches to consider the interaction between socioeconomic and climate systems. It shows how the impact can differ in cases in which climate change mitigation is, or is not, considered. To the author's knowledge, this is the first attempt to consider such an interrelationship in analyzing the socioeconomic impacts of climate-change-induced decline in labor productivity.

1.2. Literature review

Some recent works have considered the interactions between socioeconomic and climate systems within climate change studies (Collins et al., 2015; Mercure et al., 2018; Monier et al., 2018; Paltsev et al., 2015; Thornton et al., 2017). These studies coupled a socioeconomic model (e.g., partial equilibrium, computable general equilibrium [CGE], or macro-econometric) with a full or reduced-form climate model (e.g., Earth system model of intermediate complexity [EMIC]), in the process of so-called full coupling (van Vuuren et al., 2012). Such studies have mainly used land use as a connector between socioeconomic and climate systems. For example, Thornton et al. (2017) coupled the Global Change Assessment Model (a socioeconomic model) and Community Earth System model (a climate model) and used this to evaluate the Representative Concentration Pathway (RCP) 4.5 and 8.5 scenarios. In the model, biospheric impacts on ecosystem productivity were passed from the climate model to the socioeconomic model, while land-use and land-cover changes were passed back from the latter to the former. One of their findings, by considering the interactions, was that global crop prices would drop around 15%–20% on average in 2100. Mercure et al. (2018) coupled two socioeconomic models (macro-econometric and technology diffusion) and a climate model (a carbon cycle and atmosphere circulation model of intermediate complexity) to evaluate the pathways to achieve the Paris Agreement and 2 °C global warming targets. In this coupling, environmental impacts obtained from socioeconomic models are input into the climate model, and land productivity obtained from the climate model is input into the socioeconomic models.

As this type of integration of models of different disciplines is

important for climate change analysis, and land use is a key connecting point, other factors are also central for considering the interactions between human and climate systems, as mentioned in the previous section. The impact of climate change on labor productivity is one such important impact. Hot weather generally affects human activities and increases the risk of heat-related illness. Hot working environments also affect workers (Kjellstrom et al., 2009b; Li et al., 2016; Tawatsupa et al., 2013; Xiang et al., 2014); not only outdoor but also indoor workers (Kjellstrom, 2016; Kjellstrom et al., 2009b, 2013). In many places, the thermal environment cannot be sufficiently controlled and intensity of physical activity is determined based on the type of work (Takakura et al., 2017). Reducing work intensity or increasing the frequency of short breaks is an adaptive action for workers as a measure to prevent heat-related effects (Kjellstrom et al., 2009b; National Institute for Occupational Safety and Health, 2016). However, such interventions lead to reduced working hours and reduced labor productivity (Donadelli et al., 2017; Dunne et al., 2013; Kjellstrom et al., 2009a; Suzuki-Parker and Kusaka, 2016; Takakura et al., 2017); hot weather can thus be a cause of economic loss (Donadelli et al., 2017; Nagy et al., 2018; Rezai et al., 2018; Roson and Sartori, 2016; Takakura et al., 2017; Zhang et al., 2018). Heat stress has already reduced labor capacity to an estimated 90% in peak months over the past few decades (Dunne et al., 2013). Notably, the impact is greater for outdoor workers such as agricultural workers than for indoor workers such as office workers (Kjellstrom et al., 2009b). Temperature increases and climate change aggravate this effect. Many studies have, through changes in labor productivity on socioeconomic activities, evaluated the impact of temperature and climate change (Dunne et al., 2013; Hsiang, 2010; Hyatt et al., 2010; Kjellstrom et al., 2009b, 2013; Kjellstrom, 2016; Roson and Sartori, 2016; Roson and van der Mensbrugghe, 2012; Suzuki-Parker and Kusaka, 2016; Takakura et al., 2017, 2018; Xia et al., 2018). Literature reviewed here is, thus, closely related to the present study. Kjellstrom et al. (2009b), the earliest study on this topic at a global scale, estimated the relationship between work capacity and weather conditions, and evaluated the future loss of labor work capacity due to climate change. That estimation of the relationship was for various work intensities (200–500 W). The authors showed that the greatest absolute losses of labor work capacity were in Southeast Asia, Latin and Central America, and the Caribbean. Suzuki-Parker and Kusaka (2016) estimated safe hours for heavy and light labor in Japan (Tokyo and Osaka) in the future and found a projected decrease, by 30%–40% and 60%–80% by the end of this century for light labor and heavy labor, respectively. Kjellstrom (2016) evaluated economic losses due to heat-exposure-induced labor productivity effects in 24 countries by 2050, and found the greatest loss in Southeast Asian countries. Roson and van der Mensbrugghe (2012) used their CGE model to evaluate GDP loss caused by declining labor productivity. Their study simultaneously assessed not only labor productivity, but also other impacts caused by climate change. Their study with a climate change (temperature increase) scenario showed that GDP loss from labor productivity change was negative in most regions (the region that suffered the highest impact experienced greater than a 6% loss), except for Europe, which received GDP gains (<1%). Roson and Sartori (2016) updated the relationship between labor productivity and climate conditions from Kjellstrom et al. (2009b) and estimated the impact of temperature increases on GDP, through decline in labor productivity for 140 regions.² They used the Global Trade Analysis Project (GTAP)

² Roson and Sartori (2016) considered not only labor productivity, but also other factors as the impact of climate change on GDP.

database version 9 for these estimates and showed labor productivity would be lower for high-temperature scenarios than for low-temperature scenarios, and lower for the agricultural sector than the manufacturing and service sectors; for example, the mean percentage variation was -2.52 to -17.48% in the agricultural sector.³ Takakura et al. (2017) also evaluated impact of heat-related-illness prevention on GDP, through worker breaks associated with climate change. Their study used the CGE model, similar to the present study, with multiple socioeconomic conditions (based on Shared Socioeconomic Pathways (Riahi et al., 2017)), climate change scenarios (based on Representative Concentration Pathways (van Vuuren et al., 2011a)), and general circulation models. They also conducted sensitivity analyses for working hours. They found total global GDP losses in 2100 would be around 2.6% – 4.0% for no-mitigation scenarios, but such losses would be less than 0.5% for the 2°C global warming scenario. They also showed the relationship between the GDP losses and global average temperature rise was roughly linear. Takakura et al. (2018) also evaluated the occupational health costs of heat exposure and the plausibility of a working time shift to offset the costs, with a similar framework to Takakura et al. (2017). They showed the outdoor labor capacity during the 2090s would be 0.54 under the highest-emission scenario and the required working time shift (to an earlier time) to maintain the labor capacity of the base year would be 5.7 h, which is implausible. Finally, Xia et al. (2018) used an input–output model to evaluate the macroeconomic impacts of heat waves in the Chinese city of Nanjing. They found a heat wave in 2013 caused a 3.43% reduction of the gross production in the city.

As shown above, a number of studies have evaluated the relationship between climate change, or heat stress, and economic losses through decline in labor productivity. However, these studies do not consider the interaction between socioeconomic and climate systems, but rather see the relationship between climate change and economic impact as unidirectional (the economic impact was calculated with given climate conditions), though an interaction is in fact occurring and therefore is important.

2. Material and methods

2.1. Study design

This study analyzed the socioeconomic impact of climate change through changes (declines) in labor productivity at the global scale for three scenarios: business-as-usual (BaU), 2°C (S2), and RCP4.5 (S45). Among these, S2 and S45 are emission reduction scenarios (see section 2.4 for the details).

Two models were used for the scenario analyses: (1) a CGE model—the Economic Projection and Policy Analysis (EPPA) model version 6 (Chen et al., 2015; Monier et al., 2018), for socioeconomic analysis, and (2) a simple climate model—the Model for the Assessment of Greenhouse Gas Induced Climate Change (MAGICC) version 6, for climate analysis (Meinshausen et al., 2011a, 2011b). These two models were coupled through the relationship between climate change and labor productivity (Fig. 1). First, the CGE model was used to calculate economic activity levels, including energy supply and GHG emissions, under the assumed scenarios mentioned above. MAGICC was then applied to calculate climate conditions with the GHG emissions obtained from the CGE analysis. The calculated climate change levels were then input into the CGE model using the relationship between climate change and labor

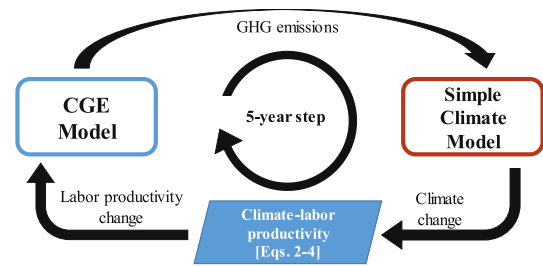


Fig. 1. Study framework; first step of the model calculation is 3 years.

productivity as a connector. In this way, the vital interaction between socioeconomic and climate conditions was considered.

The CGE model was run from 2007 to 2100, mostly with 5-year time steps (2007, 2010, 2015, ... 2100). MAGICC has traditionally been used with integrated assessment models (Thomson et al., 2011), but two-way interactions were not considered there. MAGICC can be run using multi-model-ensemble emulations for climate parameters and carbon cycle settings (171 in total). In the present study, outputs of the 17th, 50th, and 83rd percentiles of the ensemble emulations were used for the BaU scenario; hereinafter, these cases are called BaU_L, BaU_M, and BaU_H, respectively (L: low; M: median; and H: high). Only the median cases (S2_I and S45_I, where I represents impact) were used for the emission reduction scenarios.

2.2. CGE model

An economic model was used to analyze future scenarios from various socioeconomic perspectives. This model, the EPPA model, is a multi-regional, multi-sectoral recursive dynamic CGE model on a global scale, with energy and environmental (GHG and air pollutant emissions) components (Chen et al., 2015; Monier et al., 2018). Below is a basic description of the model based on Chen et al. (2015).⁴

The input–output structure for regional economies and international trade of the model is based on the GTAP database version 8 (2007 data).⁵ The model is calibrated with the GTAP data, but further calibrated until 2015, based on the World Economic Outlook (International Monetary Fund, 2013) and World Energy Outlook 2012 (International Energy Agency, 2012). Although the original GTAP has 129 regions and 57 sectors, they are aggregated into 18 and 14, respectively (Table 1).

The model has three types of agent: production sectors, households, and governments. Production sectors (i.e., the sectors in Table 1) produce goods and services from primary factors (labor, capital, and natural resources) and intermediate inputs. They supply goods and services to other production sectors as intermediate inputs, and households and government as final demand. Production sectors determine their production levels to minimize the production cost.

Households own primary factors, provide them to production sectors, and receive income. Households determine their consumption to maximize the utility. Each country has one aggregated household.

Governments collect taxes from production sectors and households to finance government expenditures.

³ In this study, GDP loss was shown as the aggregated impact of various climate change impacts, but heat stress was the dominant factor in 34 regions (Tables A1.1 and A1.2 of Roson and Sartori (2016)).

⁴ The EPPA model is downloadable for free from: <https://globalchange.mit.edu/research/research-tools/human-system-model/download>.

⁵ For more information about the GTAP data, refer to the GTAP website: <https://www.gtap.agecon.purdue.edu/databases/v8/default.asp>.

Table 1
Definitions of regions and sectors in the computable general equilibrium model.

| Code | Region | Code | Sector |
|------|----------------------------------|------|-----------------------------|
| USA | United States | CROP | Agriculture - crops |
| CAN | Canada | LIVE | Agriculture - livestock |
| MEX | Mexico | FORS | Agriculture - forestry |
| JPN | Japan | FOOD | Food products |
| ANZ | Australia, New Zealand & Oceania | COAL | Coal |
| EUR | European Union+8 | OIL | Crude oil |
| ROE | Eastern Europe and Central Asia | ROIL | Refined oil |
| RUS | Russia | GAS | Gas |
| ASI | East Asia | ELEC | Electricity |
| KOR | South Korea | EINT | Energy-intensive industries |
| IDZ | Indonesia | OTHR | Other industries |
| CHN | China | DWE | Ownership of dwellings |
| IND | India | SERV | Services |
| BRA | Brazil | TRAN | Transport |
| AFR | Africa | | |
| MES | Middle East | | |
| LAM | Latin America | | |
| REA | Rest of Asia | | |

Note: The electricity sector consists of various power generation technologies, including thermal, nuclear, hydro, solar, wind, biomass, and other renewable energy sources.

Source: [Chen et al. \(2015\)](#).

As with typical CGE models, the activities of different agents and their interactions are described by three types of condition: zero-profit conditions; market-clearing conditions; and income-balance conditions. Zero-profit conditions describe cost-benefit analyses for economic activities. Market-clearing conditions determine price levels that equalize market demand and supply. Income-balance conditions specify income levels of households and governments that support their expenditures.

Similar to many CGE models (e.g., [Li and Masui, 2019](#); [Matsumoto and Andriosopoulos, 2016](#); [Yu et al., 2018](#)), this model also applied nested constant elasticity of substitution (CES) functions to specify preferences and production technologies. CES functions can be written as Eq. (1), which shows an example of a CES production function assuming goods or services in sector s are produced using labor (L), capital (K), and intermediate inputs (M) as the inputs.

$$Prod_s = A_s (sl_s L_s^{\rho_s} + sk_s K_s^{\rho_s} + sm_s M_s^{\rho_s})^{\frac{1}{\sigma_s}} \quad (1)$$

where $Prod_s$: quantity of production, A_s : scale parameter, sl , sk , and sm : share of each input ($sl + sk + sm = 1$), ρ : substitution parameter ($= (\sigma - 1)/\sigma$), σ : elasticity of substitutions.

Regarding the environmental aspect, the model considers emissions of carbon dioxide (CO₂), non-CO₂ GHGs, and other air pollutants (sulfur oxides, nitrogen oxides, carbon monoxide, ammonia, non-methane volatile organic compounds, black carbon, and organic carbon). These gases are emitted from the activities of industrial and final demand sectors (i.e., energy use and production processes). Carbon prices are calculated when reducing emissions from the BaU scenario.

Future scenarios are calibrated to specified energy or emission profiles, or driven by economic growth and by exogenously specified efficiency improvements in labor, energy, and land use. Demand for goods and services produced from each sector increases as GDP and income grow. Stocks of limited resources—such as coal, oil, and natural gas—deplete with their use, which increases production costs. Sectors that use renewable resources compete for the available flow of services from them, generating rents. The production structure for electricity is detailed (i.e., types of power source are considered; see [Table 1](#) footnote), and captures

technological changes. The deployment of advanced technologies is endogenous. Advanced technologies can enter the market when they become cost-competitive with existing technologies. Technologies are ranked in accordance with their levelized cost of electricity. Low-carbon technologies are introduced when a carbon price exists. Initially, a fixed factor is required to represent costs of deployment (e.g., institutional costs and learning costs) for new technologies that require time to penetrate into the market. The fixed-factor supply grows each period as a function of deployment until it becomes non-binding, allowing for large-scale deployment of the new technology.

The model is run with the above assumptions and the socioeconomic scenarios shown in section 2.4. For the emission reduction scenarios, global emission pathways between the base year and 2100 are given as constraints, while such constraints are not applied to the BaU scenario. In the model, global emissions trading is taken into account when reducing emissions. The total annual global emission allowances are equal to the global emission level in each year of the target emission pathway. Emission allowances are allocated to each region in proportion to their projected population from the year 2050 onwards. Between the base year and 2050, the share of emission allowances of each region is set by linear interpolation between the observed emissions in the base year and the assigned emission allowances for 2050. A complete description of the original model and its structure are in [Chen et al. \(2015\)](#).

The present study modified the original EPPA model to express the impact of climate change on labor productivity in the model. To do this, the relationship obtained from [Kjellstrom et al. \(2009a, 2009b\)](#) and [Roson and Sartori \(2016\)](#) was introduced in the model (Eqs. (2)–(4)).⁶ These equations are defined by three parts: (1) a lower threshold of temperature, below which no climate impact appears; (2) decline in labor productivity by temperature increases; and (3) a minimum level of labor productivity above the higher threshold. Following [Roson and Sartori \(2016\)](#), the equations are prepared for three groups of sectors—agriculture, manufacturing, and service—though in reality the impacts on labor productivity are more detailed within each group. The shape of equations and the minimum level of labor productivity are the same for all sectors, but the lower and higher thresholds of temperature differ by sector. The agricultural sector is more sensitive to temperature than the service sector. Monthly, daily, or even sub-daily temperature data have been applied when calculating the changes in annual labor productivity in a year ([Kjellstrom et al., 2009b](#); [Roson and Sartori, 2016](#); [Takakura et al., 2017](#)). Because of data availability, the present study follows [Roson and Sartori \(2016\)](#), which used the monthly data and averaged monthly changes in labor productivity for obtaining the annual values. The average monthly temperature for the base year was also obtained from [Roson and Sartori \(2016\)](#).

$$\begin{aligned} lab_{agr,r} &= 1.0 \quad (temp_r \leq 26) \\ lab_{agr,r} &= 1.0 - \frac{1.0 - 0.25}{36 - 26} (temp_r - 26) \quad (26 < temp_r \leq 36) \\ lab_{agr,r} &= 0.25 \quad (temp_r > 36) \end{aligned} \quad (2)$$

⁶ The original version of the estimates was by [Kjellstrom et al. \(2009a, 2009b\)](#), and was revised by [Roson and Sartori \(2016\)](#). These estimates are on the global scale.

$$\begin{aligned}
 lab_{man,r} &= 1.0 \quad (temp_r \leq 28) \\
 lab_{man,r} &= 1.0 - \frac{1.0 - 0.25}{43 - 28} (temp_r - 28) \quad (28 < temp_r \leq 43) \\
 lab_{man,r} &= 0.25 \quad (temp_r > 43)
 \end{aligned} \tag{3}$$

$$\begin{aligned}
 lab_{ser,r} &= 1.0 \quad (temp_r \leq 30) \\
 lab_{ser,r} &= 1.0 - \frac{1.0 - 0.25}{50 - 30} (temp_r - 30) \quad (30 < temp_r \leq 50) \\
 lab_{ser,r} &= 0.25 \quad (temp_r > 50)
 \end{aligned} \tag{4}$$

where *lab*: labor productivity, *temp*: temperature, *agr*: agricultural sector, *man*: manufacturing sector, *ser*: service sector, *r*: region.

By running the model, with the above data and the scenarios (section 2.4), we get outputs such as economic activities, energy supply, and emissions. The model was developed with the General Algebraic Modeling System (GAMS) software using the mathematical programming system for general equilibrium analysis (MPSGE) modeling framework.

2.3. MAGICC

MAGICC is a simple climate model developed by Wigley and Raper (1992, 1987) and has since been updated (Wigley et al., 2009). Meinshausen et al. (2011a, 2011b) develop the model's current version 6. The following explanation of the model is based on Meinshausen et al. (2011a) and the model's website.⁷

MAGICC has a hemispherically averaged upwelling-diffusion ocean coupled with an atmosphere layer and a globally averaged carbon cycle model. Similar to most other simple climate models, MAGICC evolved from a simple global average energy-balance equation. Equation (5) shows that equation for the perturbed climate system.

$$\Delta Q_G = \lambda_G \Delta T_G + \frac{dH}{dt} \tag{5}$$

where ΔQ_G : global-mean radiative forcing at the top of the troposphere. This extra energy influx is partitioned into increased outgoing energy flux and heat content changes in the ocean dH/dt . The outgoing energy flux is dependent on the global-mean feedback factor, λ_G , and the surface temperature perturbation ΔT_G .

In the model, GHG concentrations are calculated based on GHG emissions. Radiative forcing is then calculated based on the GHG concentrations. Finally, global and hemispheric climate responses are calculated from the radiative forcing. The terrestrial and ocean carbon cycle is considered in these calculations (Fig. A1 in Meinshausen et al. (2011a)). As explained in section 2.1, the model can be run using multi-model-ensemble emulations for climate parameters and carbon cycle settings.

A complete description of the model, including equations of each component, can be found in Meinshausen et al. (2011a)⁸

2.4. Future scenarios

Using the CGE model and MAGICC, three scenarios with and without climate change impacts were analyzed: the BaU scenario

and two emission reduction scenarios (S2 and S45). With the BaU scenario, the impact of climate change on socioeconomic conditions was analyzed through labor productivity when no climate policies were considered. With the emission reduction scenarios, the impact when mitigation policies were introduced was analyzed.

The BaU scenario follows the original BaU scenario of the EPPA model. The model used various sources for near- and long-term projections of the world economy, including GDP, population, and energy technology (Energy Information Administration, 2010; Gitiaux et al., 2012; Gordon, 2012; International Monetary Fund, 2013; Paltsev et al., 2005; United Nations Population Division, 2013; World Bank, 2013). See Chen et al. (2015) for the details of the BaU scenario of the EPPA model. Figure 2 shows population, GDP, and primary energy supply for that scenario (without climate change impact). In this scenario, the global population is assumed to grow from 6.7 billion in the base year to 10.9 billion in 2100 (Fig. 2a). Population will undergo an especially profound increase in Africa. The total global GDP will substantially expand from 55.6 trillion USD in the base year to 423.7 trillion USD in 2100 (Fig. 2b). Total primary energy supply will increase from 497.7 EJ in the base year to 1119.5 EJ in 2100 (Fig. 2c and d), though at a lower rate than for GDP. Energy supply will greatly increase in China (Fig. 2c). Among energy sources, the share of fossil fuels will be largest, and increase in natural gas will be considerable (Fig. 2d). The resulting global average temperature rise from the pre-industrial level will be around 3.25–4.49 °C.

For the two climate change mitigation scenarios, S2 is that for controlling emissions to realize a 2 °C temperature rise by 2100 (Matsumoto et al., 2018), while S45 is to control emissions, aimed at radiative forcing of 4.5 W/m² in 2100 (Thomson et al., 2011). Thus, S2 corresponds to the mitigation target of the Paris Agreement (Bataille et al., 2018), while S45 is an intermediate mitigation scenario (Matsumoto et al., 2016). Fig. 3 shows CO₂ emissions for the three scenarios. S2 shows a greater reduction of emissions than S45. In both scenarios, the same settings as with the BaU scenario were used for future assumptions such as population growth and autonomous energy efficiency improvement, while GDP and other economic activities are calculated using the CGE model.

3. Results and discussion

Numerous studies have analyzed economic and energy impact of emission reduction scenarios, including with the 2 °C target, using various models, including CGE models (Bertram et al., 2015; Fujimori et al., 2014; Masui et al., 2011; Matsumoto, 2015; Matsumoto et al., 2016, 2018; Matsumoto and Andriosopoulos, 2016; Matsumoto and Masui, 2011; Matsumoto and Shiraki, 2018; Okagawa et al., 2012; Rasiah et al., 2017; Riahi et al., 2015, 2017; Thomson et al., 2011; Van Vliet et al., 2012; van Vuuren et al., 2011b). The focus is therefore on results comparing cases with and without the impact of climate change, but not the socioeconomic impact of climate change mitigation.

First, Fig. 4 shows how climate change affects labor productivity in each region by scenario and sector. Labor productivity declines over time because climate change progresses. This productivity was lowered in the agricultural sector, while decreases were not considerable in the manufacturing and service sectors. Comparing among the scenarios, BaU_M showed the higher impact than the emission reduction scenarios. This is because BaU experienced a greater amount of climate change. The range of labor productivity in 2100 was 0.75–1.00 (BaU_M), 0.89–1.00 (S2_I), and 0.85–1.00 (S45_I) for the agricultural sector. High-temperature regions, such as India, Indonesia, and the Middle East, were substantially affected. In BaU_M, for example, labor productivity of the

⁷ MAGICC website: <http://www.magicc.org/>.

⁸ An online version of MAGICC is available for free from: <http://live.magicc.org/>.

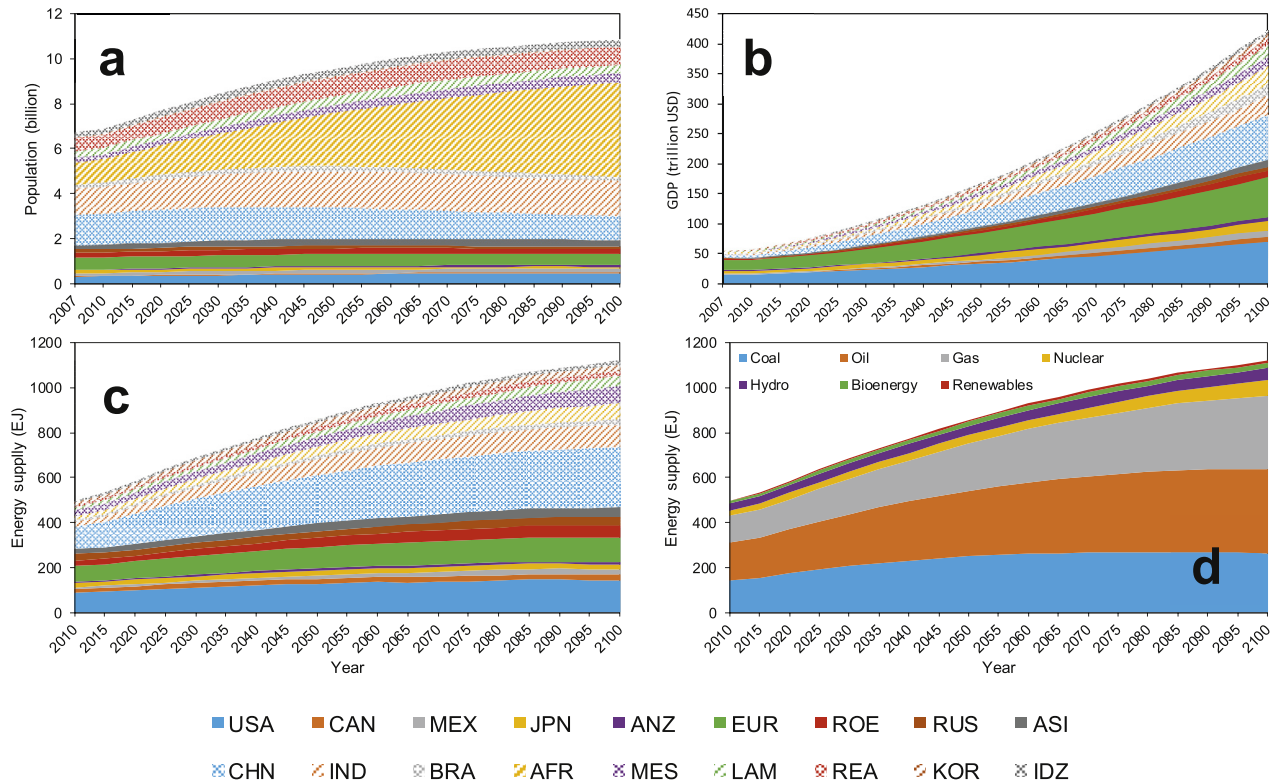


Fig. 2. Properties of the BaU scenario from the base year to 2100: (a) population, (b) gross domestic product, (c) primary energy supply by region, and (d) primary energy supply by source. The legend for panels (a)–(c) is shown at the bottom.

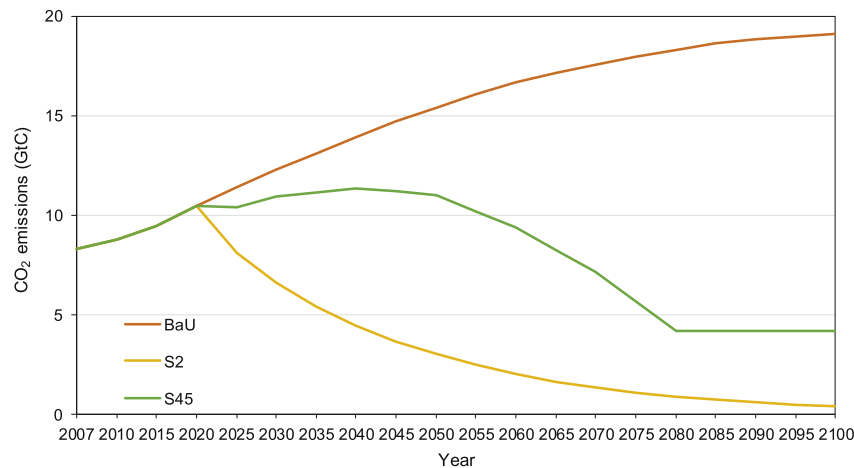


Fig. 3. CO₂ emissions from fossil fuels and industrial process for the BaU, S2, and S45 scenarios.

agricultural sector in 2100 was 0.75, 0.81, and 0.82 in Indonesia, India, and the Middle East, respectively. However, some low-temperature countries, such as Canada, were completely unaffected by future climate change because their climate levels did not attain the lower threshold in all months, even though climate change does occur.

As a result of the decreased labor productivity shown above, socioeconomic activities were affected in various ways. Fig. 5 shows the time-series global GDP levels relative to the corresponding no-impact cases. As can be seen, the impact of climate change on the total global GDP was negative and gradually expanded over time.

Decreases in labor productivity reduce production and overall economic activities, and such decreases become larger over time as climate change advances. Obviously, scenarios with high temperatures were negatively affected more than those with low-temperature-impact scenarios. This is because of the greater impact on labor productivity (Fig. 4). For example, within the BaU cases, GDP was 0.53%–0.91% lower at the global level in 2100 when considering the impact of climate change. However, the impact was low, at approximately –0.1% in 2100, for the S2_I case.

However, the impact on GDP differed by region (Table 2 and Fig. 6). The obvious tendency was that high-temperature regions

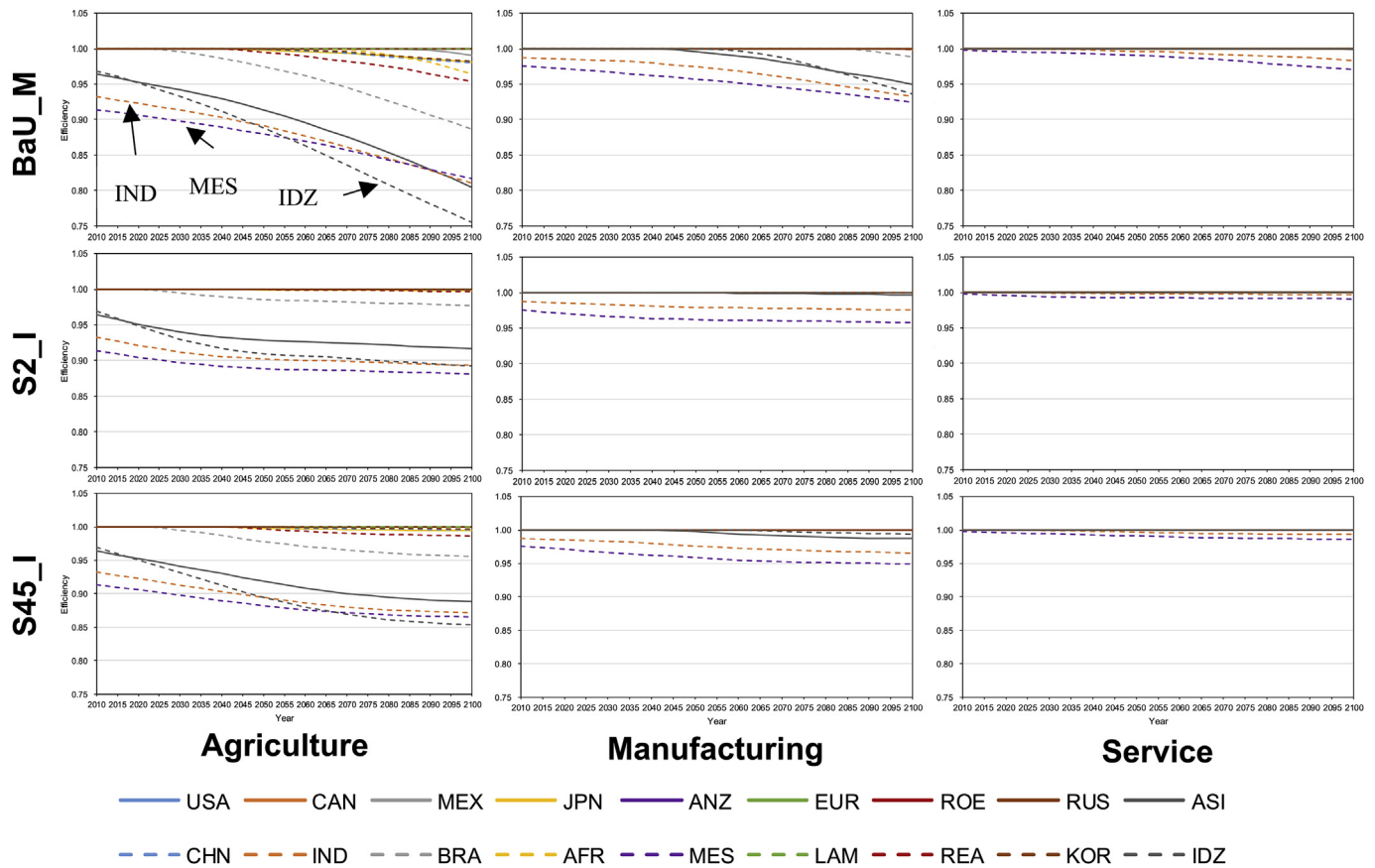


Fig. 4. Labor productivity impact by scenario and sector. Labor productivity of 1.00 means there is no influence of climate change. For the BaU scenario, only BaU_M is shown.

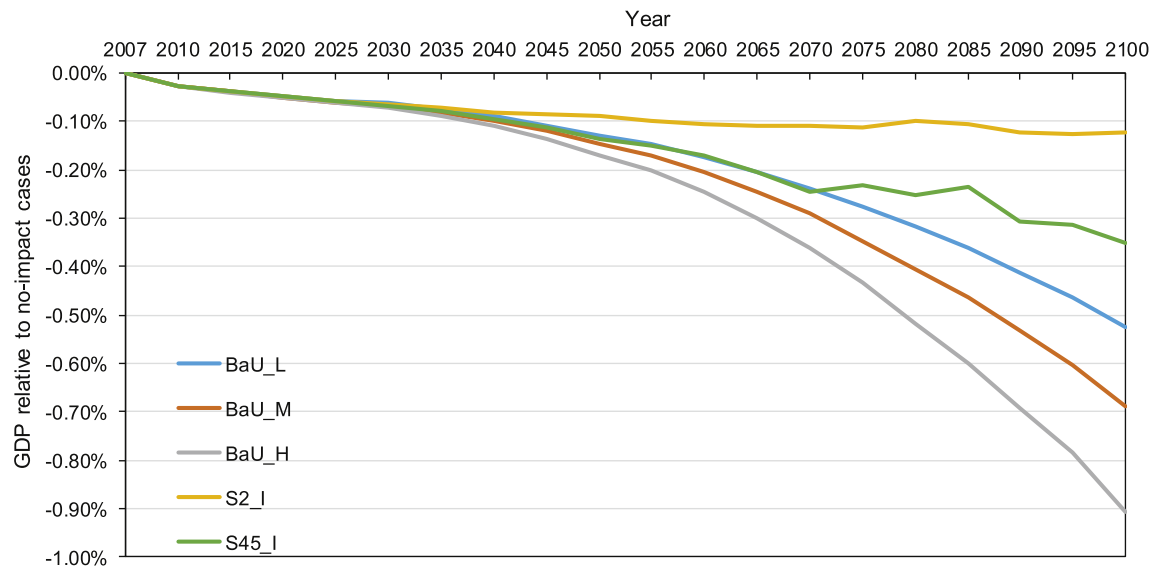


Fig. 5. Global gross domestic product levels relative to the corresponding no-impact cases. BaU_L, BaU_M, and BaU_H were compared with BaU without climate change impact, S2_I was compared with S2 without climate change impact, and S45_I was compared with S45 without climate change impact.

suffered largely from climate-change-induced labor productivity changes, although the degrees varied by region. In Indonesia, where the impact was the world's largest in 2100, GDP was 6.12% smaller for BaU_H and 1.82% smaller for S2_I than the corresponding no-impact cases; again, scenarios with severer climate change caused greater GDP reduction. In the high-temperature

regions, labor productivity decreases caused reduced production in all sectors, resulting in weakening of all economic activities, including consumption, investment, and trade (see Figs. 7 and 8 for trade). In particular, agricultural countries, such as Indonesia, incur large economic impact relative to non-agricultural countries because the highest impact of climate change on labor productivity

Table 2

Gross domestic product levels relative to the corresponding no-impact cases in 2100 by region.

| | BaU_L | BaU_M | BaU_H | S2_I | S45_I |
|-------|--------|--------|--------|--------|--------|
| USA | 0.09% | 0.12% | 0.16% | 0.01% | 0.07% |
| CAN | −0.02% | −0.02% | 0.01% | −0.03% | 0.12% |
| MEX | −0.04% | −0.07% | −0.11% | 0.11% | −0.08% |
| JPN | 0.03% | 0.04% | 0.14% | 0.08% | 0.03% |
| ANZ | −0.04% | −0.04% | −0.05% | −0.05% | 0.02% |
| EUR | 0.10% | 0.14% | 0.19% | 0.13% | 0.10% |
| ROE | −0.05% | −0.07% | −0.09% | −0.07% | 0.04% |
| RUS | −0.31% | −0.40% | −0.52% | −0.13% | 0.01% |
| ASI | −0.88% | −1.14% | −1.75% | −0.22% | −0.56% |
| CHN | −0.39% | −0.61% | −0.85% | −0.03% | −0.13% |
| IND | −3.99% | −4.85% | −5.92% | −1.52% | −3.32% |
| BRA | −0.16% | −0.23% | −0.33% | −0.04% | −0.08% |
| AFR | −0.25% | −0.59% | −1.20% | −0.15% | −0.19% |
| MES | −1.30% | −1.61% | −1.99% | 0.04% | −0.71% |
| LAM | 0.00% | 0.01% | 0.00% | 0.00% | 0.02% |
| REA | −0.53% | −0.87% | −1.30% | −0.02% | −0.31% |
| KOR | 0.00% | −0.01% | −0.04% | −0.04% | 0.07% |
| IDZ | −4.13% | −5.02% | −6.12% | −1.82% | −2.84% |
| World | −0.53% | −0.69% | −0.91% | −0.12% | −0.35% |

Note: BaU_L, BaU_M, and BaU_H were compared with BaU without climate change impact, S2_I was compared with S2 without climate change impact, and S45_I was compared with S45 without climate change impact.

regions, it is not necessarily true that such regions had a small negative or positive effect. Russia, for example, is one of the coldest regions in the world, but its negative impact was higher than in some warmer countries⁹. This is attributed to changes in trade (Figs. 7 and 8, and Table 3). For Russia, import increased (0.17% in 2100) while export decreased (−0.52% in 2100) for the BaU_M case (Table 3); thus, trade worked as a cause of GDP loss. Export reduction occurred because of a large negative impact on economic activities, particularly in high-temperature regions, and decreased export to these regions.

Fig. 9 shows the total global primary energy supply relative to the corresponding no-impact scenarios. Among the BaU groups, the impact's direction was similar to that of GDP impact (Fig. 5); that is, the severe climate change case had a greater impact. However, in comparing the scenarios, tendencies for total global GDP were not seen. For S45_I, the value fluctuated around −0.05% to 0.00% but was relatively stable throughout the study period. For S2_I, however, the value was similar to that in S45_I until 2080, but decreased from then to reach around −0.25% in 2100.

Then, observing the primary energy supply by source (Fig. 10), the impact completely differed by source, and the impact's directions were not consistent among scenarios. This may be due to

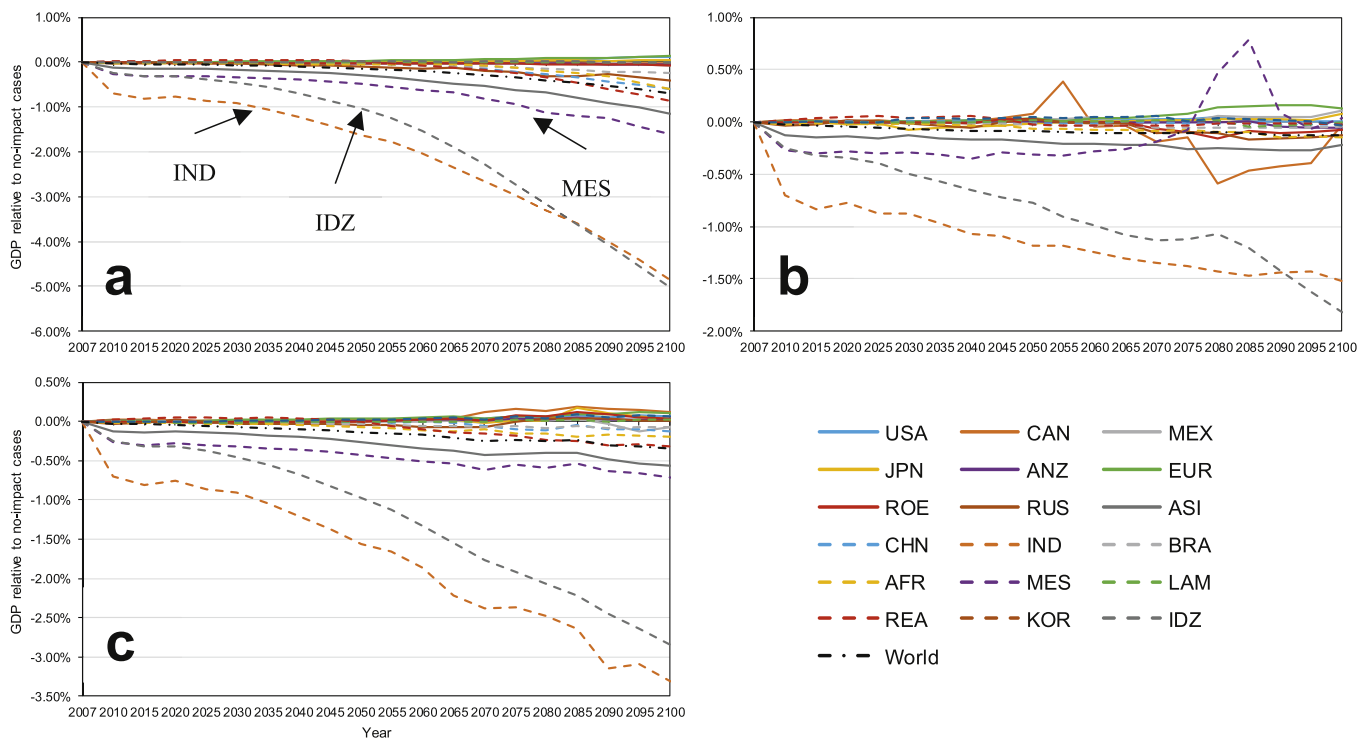


Fig. 6. Selected time series of gross domestic product levels relative to the corresponding no-impact cases by region. (a) BaU_M, (b) S2_I, and (c) S45_I.

was observed in the agricultural sector (Fig. 4).

However, GDP gains (positive GDP effects) were observed in some regions in low- or medium-temperature zones. This is attributable to comparative advantage owing to differences in labor productivity changes by region. Because of the differences, reduced production in regions that experienced larger changes in labor productivity was partly offset by production in regions with smaller changes.

Nevertheless, although negative impact tends to be lower or even positive impact was observed in low- or medium-temperature

the difference in the amount of energy used by the source and the differing energy structures among scenarios. The BaU scenarios rely on traditional fossil fuels, while the mitigation scenarios use more low-carbon energy sources. In BaU_M and S45_I, for example, declining percentage of renewable energy was greatest, as the amount of energy supply from renewable energy was small

⁹ Even in warm countries, labor productivity is unaffected if the temperature does not reach the lower threshold.

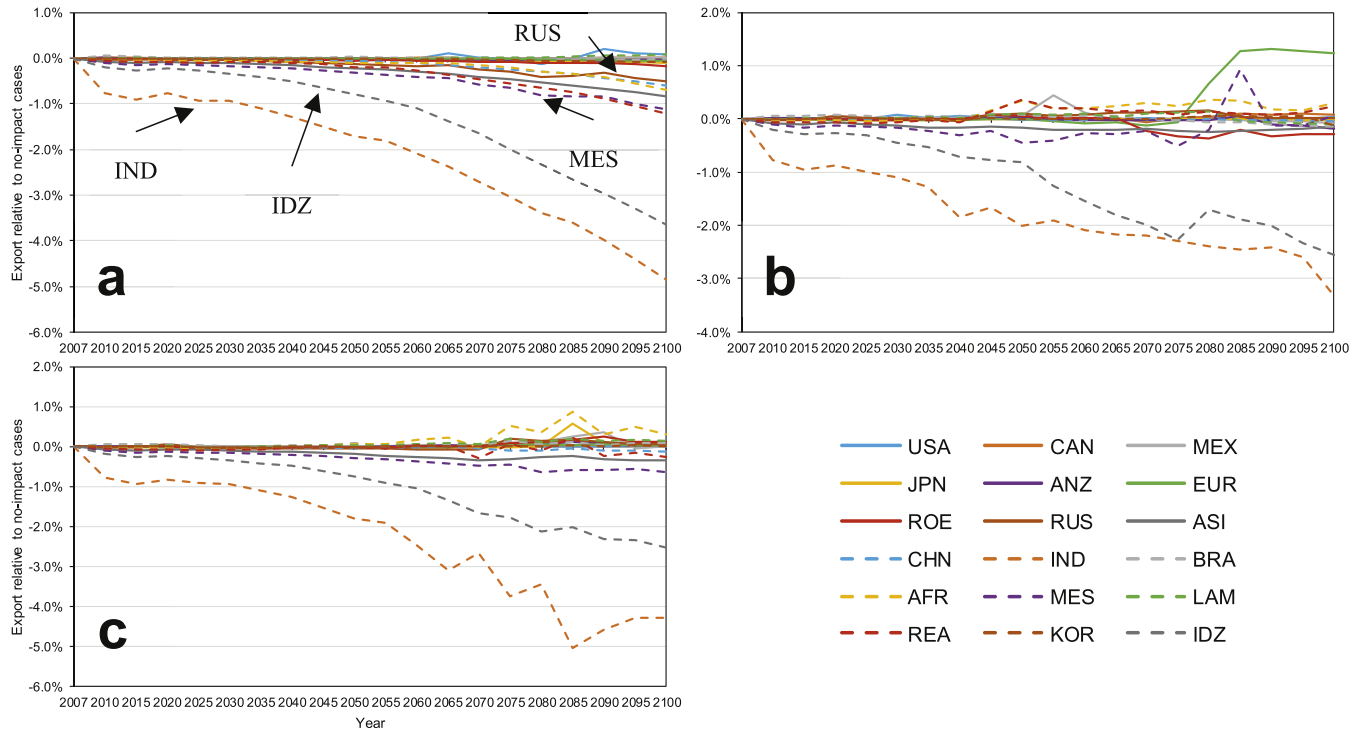


Fig. 7. Selected time series of export relative to the corresponding no-impact cases by region. (a) BaU_M, (b) S2_I, and (c) S45_I.

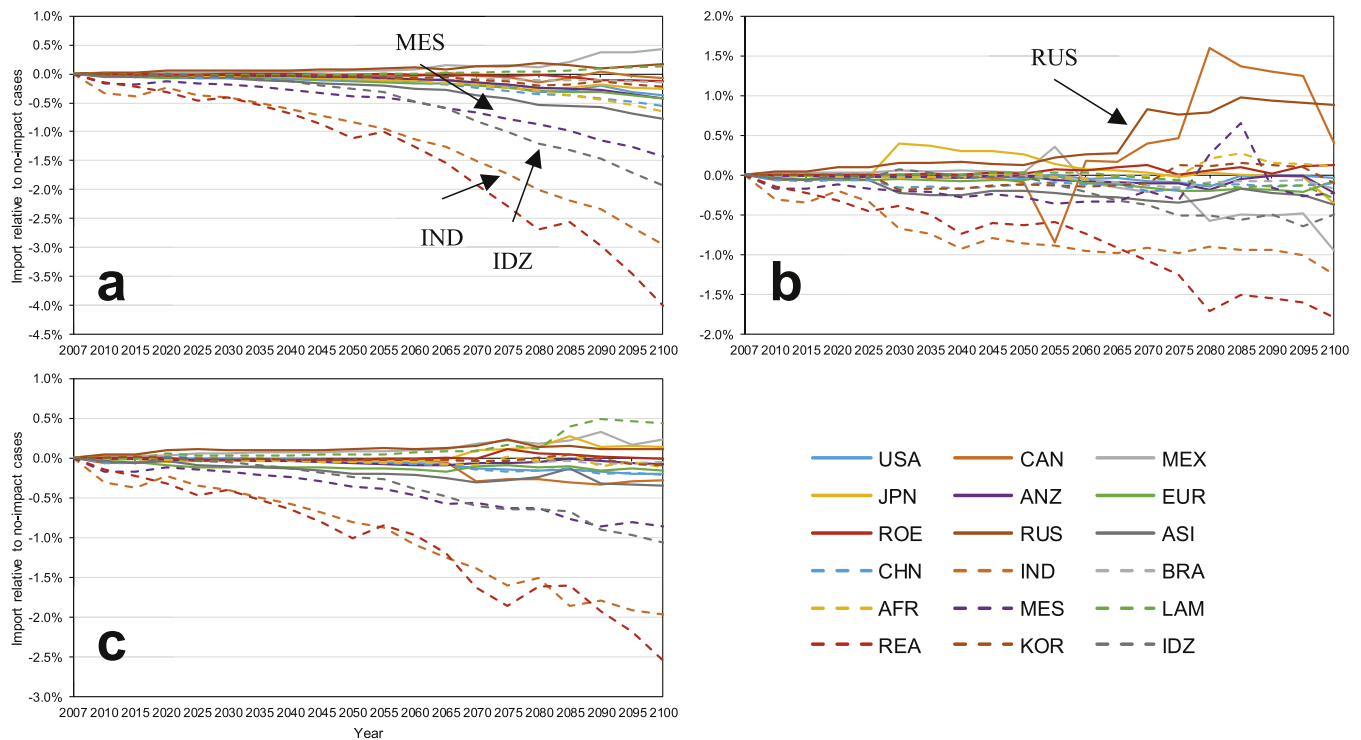


Fig. 8. Selected time series of import relative to the corresponding no-impact cases by region. (a) BaU_M, (b) S2_I, and (c) S45_I.

compared with other types of energy (see Fig. 2 for BaU). In these cases, the reduction of “amount” of renewable energy is still small. However, in S2_I, which needs the larger amount of renewable energy to achieve the strict emission reduction target, the impact

on natural gas is largest. This is due to the reduction of the amount of natural gas used in this scenario compared with the other scenarios. Straightforward tendencies observed for GDP were not shown for the total primary energy supply because of these varied

Table 3

Export and import levels relative to the corresponding no-impact cases in 2100.

| | Export | | | Import | | |
|-----|--------|--------|--------|--------|--------|--------|
| | BaU_M | S2_I | S45_I | BaU_M | S2_I | S45_I |
| USA | 0.09% | 0.03% | 0.02% | −0.37% | −0.04% | −0.20% |
| CAN | 0.01% | 0.08% | 0.12% | −0.06% | 0.40% | −0.29% |
| MEX | 0.01% | −0.09% | 0.01% | 0.43% | −0.95% | 0.23% |
| JPN | −0.10% | −0.03% | 0.04% | −0.26% | −0.36% | 0.14% |
| ANZ | −0.04% | −0.18% | 0.03% | −0.42% | −0.23% | −0.08% |
| EUR | −0.06% | 1.23% | 0.03% | −0.42% | −0.07% | −0.16% |
| ROE | −0.17% | −0.28% | 0.12% | −0.13% | 0.13% | 0.00% |
| RUS | −0.52% | 0.03% | 0.06% | 0.17% | 0.88% | 0.12% |
| ASI | −0.83% | −0.14% | −0.34% | −0.78% | −0.37% | −0.35% |
| CHN | −0.59% | −0.03% | −0.13% | −0.56% | −0.10% | −0.21% |
| IND | −4.85% | −3.33% | −4.29% | −2.95% | −1.25% | −1.96% |
| BRA | 0.00% | −0.14% | 0.09% | −0.14% | −0.17% | −0.05% |
| AFR | −0.70% | 0.31% | 0.30% | −0.65% | 0.11% | −0.12% |
| MES | −1.13% | 0.06% | −0.63% | −1.43% | −0.22% | −0.86% |
| LAM | 0.08% | −0.11% | 0.16% | 0.13% | −0.30% | 0.44% |
| REA | −1.23% | 0.24% | −0.27% | −4.01% | −1.79% | −2.54% |
| KOR | −0.09% | −0.13% | 0.01% | −0.21% | −0.11% | −0.09% |
| IDZ | −3.65% | −2.55% | −2.53% | −1.93% | −0.50% | −1.07% |

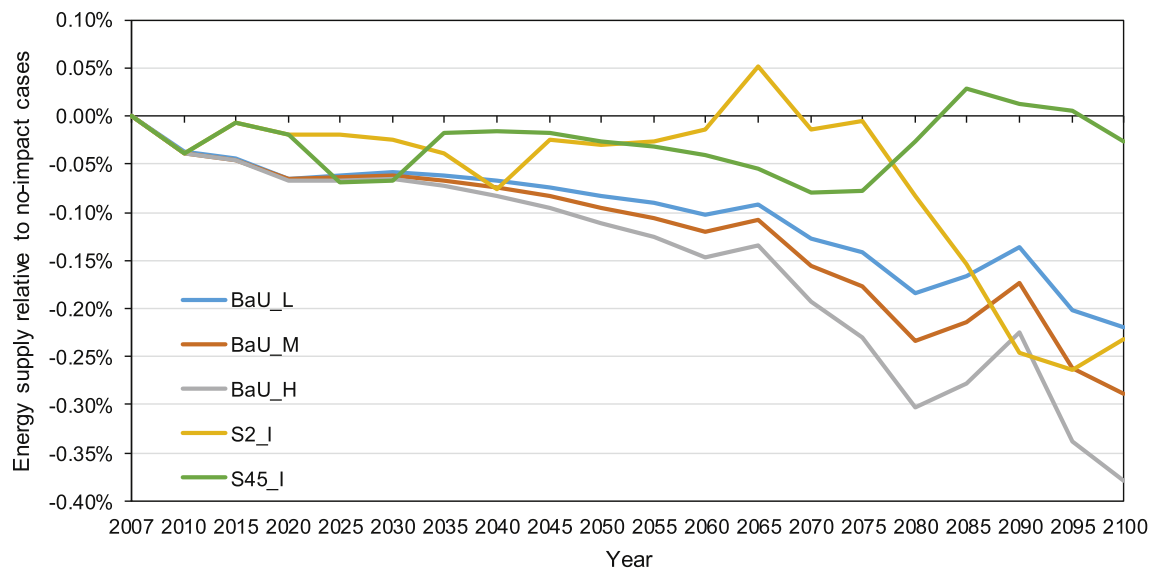


Fig. 9. Total global primary energy supply relative to the corresponding no-impact cases. BaU_L, BaU_M, and BaU_H were compared with BaU without climate change impact, S2_I was compared with S2 without climate change impact, and S45_I was compared with S45 without climate change impact.

characteristics of primary energy structure.

CO₂ emissions were also affected by the climate-change-induced labor productivity change (Fig. 11).¹⁰ As with the impact observed for total global GDP, the impact was gradually increasing and high-temperature cases were more considerably affected. The impact was around −0.25% to −0.45% in 2100.

As with GDP, the impact differed by region, even though the global emissions were identical (for S2 and S45). Table 4 shows the share of CO₂ emissions from each region in 2100. There was no large difference between the cases where the climate change impact was or was not considered, though there were some interesting findings; such as where the share increased 0.11 percentage points in China yet declined 0.29 points in India for the S2 group. These are largely attributable to the aforementioned

changes in economic activities. Promotion of production activities may increase CO₂ emissions, while reduction of such activities tends to decrease them. However, because the decline in labor productivity occurred mainly in the agricultural sector, which is not a carbon-intensive sector, the impact on CO₂ emissions was minor.

Although CO₂ emissions were reduced by considering the climate change impact on labor productivity, their impact on temperature was slight (the order of 0.01 °C). This is because the impact on CO₂ emissions was very small for the analyzed scenarios (the highest was −0.45% for BaU_H in 2100; Fig. 11).

These results suggest the impact of labor productivity through climate change on socioeconomic activities was not large at the global level. However, the variation of such impact by region was made clearer. In the analysis, high-temperature regions, such as Indonesia, India, and the Middle East, were affected negatively for the most part, while low- to medium-temperature regions were affected less, or even obtained a positive effect. Because this method of coupling multiple models is costly and time-consuming, and sometimes yields rather small returns, coupling models is not

always necessary (van Vuuren et al., 2012). However, although the effect was small in the global-scale socioeconomic impact, the regional-scale impact appeared considerable in the present study. Furthermore, because the socioeconomic impact caused by climate change has various channels—including land area, agricultural productivity, heat stress, and human health (Roson and Sartori, 2016)—socioeconomic impact from labor productivity is only one factor. This means, in consideration of various aspects of climate change, the global impact cannot be negligible. Further analysis is required with such coupled models by including the range of impacts.

Furthermore, the impacts were smaller for the low-temperature (i.e., low-emission) scenarios than for the high-temperature (i.e., high-emission) scenarios. This implies that emission reduction from earlier years can more greatly reduce the impacts, as Warren et al. (2013) also showed that early mitigation action can avoid a large proportion of the future impacts. In addition, from the perspective of mitigation costs, the costs will be smaller by starting

¹⁰ For the emission reduction scenarios (S2 and S45), the global CO₂ emissions are given in the model. Therefore, the emissions are identical both with/without climate change impact and these results are not shown in Fig. 11.

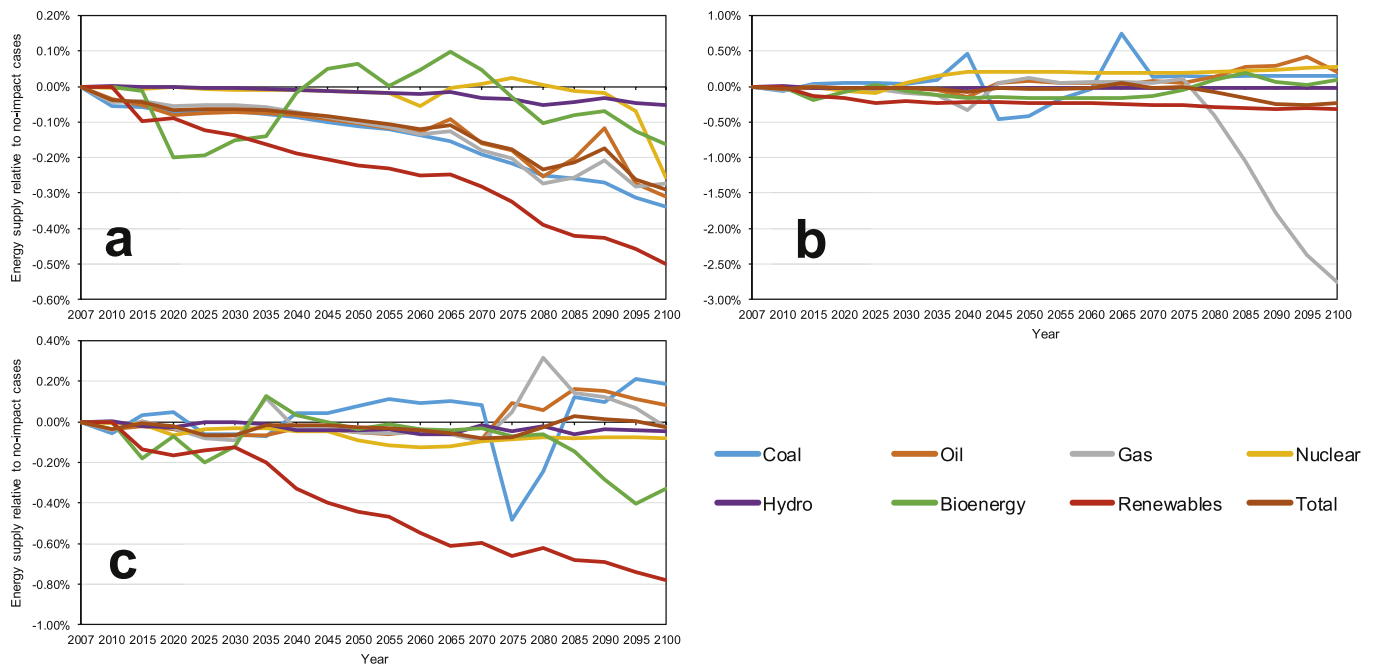


Fig. 10. Global primary energy supply by source relative to the corresponding no-impact cases. (a) BaU_M, (b) S2_I, and (c) S45_I.

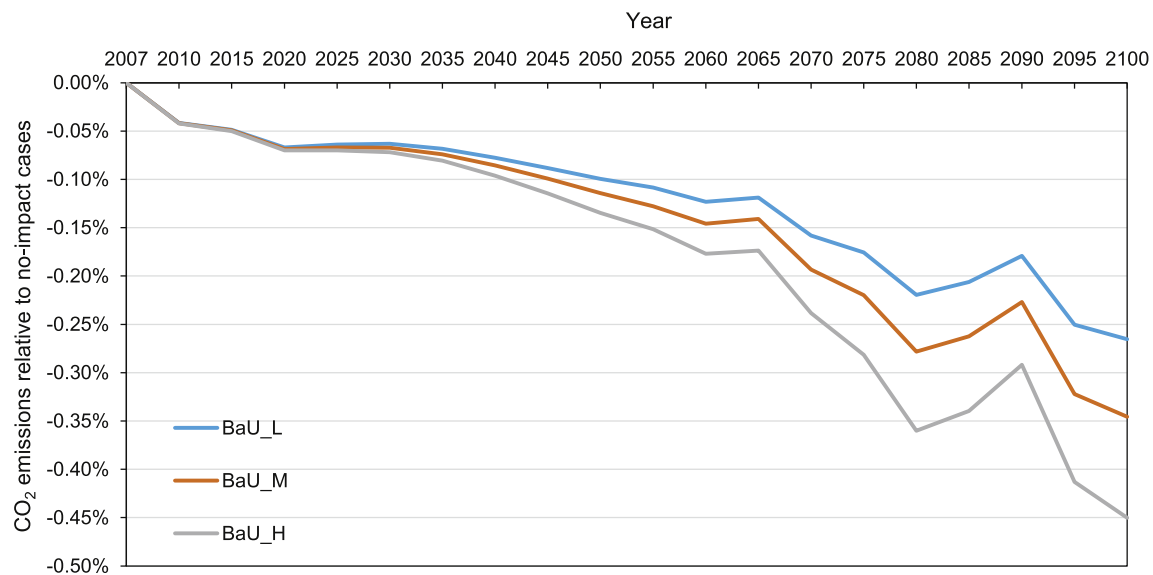


Fig. 11. Global CO₂ emissions relative to the no-impact case. The figure only shows the results for the BaU scenario because emissions are given for the S2 and S45 scenarios in the computable general equilibrium model.

emission reduction earlier, and such emission pathways can also raise the probability of achieving large mitigation targets (Jakob et al., 2012; Luderer et al., 2011, 2013; Matsumoto et al., 2018). Therefore, considering from both climate change mitigation and impact perspectives, early actions for climate change are desirable.

Takakura et al. (2017) is one notable study evaluating GDP loss due to climate-change-induced labor productivity change. Comparatively, the loss of total global GDP was small in the present study. For example, it was around -1.2% to -2% for a global average temperature rise of approximately 3°C in 2100 in Takakura et al. (2017), while it was -0.53% in the present study (BaU_L). Additionally, for regional GDP loss, GDP gain (positive GDP change) was observed in only one region (Rest of Europe) for high-emission

scenarios (RCP 6.0 and RCP 8.5); this was 1.45% – 5.29% by scenario, in Takakura et al. (2017), but was observed in several regions, such as the United States and Europe (EUR), in the present study. There are several possible reasons for such differences, but two factors seem the most important: the way of calculating labor productivity impact, and interactions between human and climate systems. For the first point, Takakura et al. (2017) applied high-resolution data (sub-daily and $0.5^\circ \times 0.5^\circ$ spatial resolutions) for calculating labor productivity change, while the present study used low-resolution (monthly and national) ones. Because climate conditions fluctuate hourly and daily, and differ by area, high/low temperatures are averaged when using monthly and national data. However, high-resolution data can be used to capture the impact of

Table 4
Share of CO₂ emissions in 2100 by region.

| | BaU | BaU_M | S2 | S2_I | S45 | S45_I |
|-----|--------|--------|--------|--------|--------|--------|
| USA | 12.16% | 12.23% | 9.40% | 9.53% | 12.53% | 12.62% |
| CAN | 1.73% | 1.75% | 1.47% | 1.46% | 0.66% | 0.69% |
| MEX | 2.23% | 2.24% | 2.02% | 2.03% | 0.61% | 0.62% |
| JPN | 1.83% | 1.85% | 3.76% | 3.78% | 3.08% | 3.10% |
| ANZ | 0.92% | 0.93% | 0.94% | 0.77% | 0.89% | 0.89% |
| EUR | 8.11% | 8.16% | 19.53% | 19.63% | 13.92% | 14.01% |
| ROE | 4.84% | 4.86% | 3.63% | 3.65% | 3.35% | 3.38% |
| RUS | 2.74% | 2.79% | 1.89% | 1.89% | 1.52% | 1.53% |
| ASI | 3.58% | 3.57% | 3.22% | 3.24% | 2.43% | 2.45% |
| CHN | 25.20% | 25.27% | 16.40% | 16.51% | 17.66% | 17.75% |
| IND | 10.92% | 10.65% | 11.90% | 11.61% | 11.82% | 11.44% |
| BRA | 1.89% | 1.89% | 3.54% | 3.55% | 2.48% | 2.49% |
| AFR | 7.27% | 7.31% | 9.93% | 9.99% | 10.66% | 10.69% |
| MES | 6.99% | 6.92% | 2.06% | 2.04% | 6.15% | 6.10% |
| LAM | 3.40% | 3.42% | 4.05% | 4.06% | 4.09% | 4.11% |
| REA | 2.13% | 2.13% | 1.59% | 1.61% | 3.15% | 3.16% |
| KOR | 2.43% | 2.45% | 2.18% | 2.19% | 2.87% | 2.89% |
| IDZ | 1.63% | 1.58% | 2.50% | 2.45% | 2.13% | 2.07% |

high temperature in one day or in part of a country. Labor productivity calculated by Takakura et al. (2017) (Fig. 2) was lower than in the present study (Fig. 4). For example, Takakura et al. (2017) showed that the lowest estimated labor productivity (explained as the worktime ratio in that study) was below 0.25 in some areas for high-intensity outdoor workers, while it was around 0.75 in the present study. This effect is the main reason for the differences between the two studies. Although using high-resolution data is ideal, the data were not applicable in the present study for considering interactions between two models. To accomplish this, an Earth system model or EMIC needs to be coupled with a socioeconomic model. This is a limitation of this study and remains a topic for future study.

For the second point, by coupling the models, GDP loss can be smaller than in the unidirectional method because decline in socioeconomic activities caused by climate impact is expected to reduce the climate impact assumed (see also section 1). As a result, GDP loss in this study may be smaller than in the prior study.

4. Conclusions and implications

4.1. Conclusions

This study evaluated climate change's impact on future economic activities through changes in labor productivity. To do so, it used the combination of the CGE and simple climate models. Economic activities were found to be negatively affected when the relationship between climate change and labor productivity was taken into account in the economic model. Although such impacts were greater in the BaU scenario, that was not the case in the 2 °C scenario. These results suggest that the larger the level of climate change, the larger the socioeconomic impact at the global level. The impact on high-temperature regions was especially notable. However, not all regions experienced economic loss due to climate change. Some regions in the low- to medium-temperature zones obtained a positive economic effect, owing to comparative advantage caused by differences in labor productivity changes among regions. These consequences were similar to those in findings from previous studies.

As shown in section 1.2, there have been studies on the relationship between climate change and labor productivity. Coupled models from different disciplines (i.e., considering these interactions), however, have recently been applied to climate change research. The present study developed new coupled modeling,

which maintains consistency between socioeconomic and climate systems by applying the relationship between climate change and labor productivity as a connector. Additionally, it used the new modeling scheme to evaluate the socioeconomic impacts of climate change. Therefore, this study serves as impetus for establishing this angle of research in climate change with regard to sustainable development.

4.2. Implications for theory and practice

From theoretical or methodological perspectives, various approaches have been applied to climate change studies, including studies on mitigation, impacts, and adaptation. Coupled models from different disciplines have recently been used in this research area as an advanced method, as in the present study. Such models have an advantage in maintaining consistency between socioeconomic and climate systems by considering the interactions for the purpose of analyzing future scenarios. This kind of methodology is, thus, a desirable approach for further evaluating and understanding the consequences of climate change and climate actions (e.g., mitigation and adaptation) on socioeconomic systems, including industry production and people's consumption. Notably, the methodology is crucial for evaluating climate change impacts, which cover various aspects of socioeconomic systems, considering the interactions that actually occur. This, in turn, ultimately contributes to achieving the Sustainable Development Goals (SDGs; e.g., SDG 13 – climate action).

From a practical perspective, this study showed that efforts for climate change mitigation will reduce the socioeconomic impacts of climate change, and these impacts will diminish with a lower climate change level. This implies early actions for emission reduction are warranted for reducing impacts in the short term and to avoid protracting the impacts over the long term. This point is also relevant with regard to the SDGs (e.g., SDG 8 – decent work and economic growth).

However, even with a large emission reduction, the impacts remain, particularly in high-temperature regions, which typically are developing economies. Therefore, in addition to the countries' own adaptation efforts, international financing for adaptation, such as the Adaptation Fund, Least Developed Countries Fund, Green Climate Fund, and Global Environmental Facility (Kameyama et al., 2016), are imperative for aiding developing economies in mitigating climate change impacts.

4.3. Limitations and future research

The main limitations of this study are the model's resolutions and the analysis of climate change adaptation. Regarding the first point, MAGICC is a simple climate model; thus, the temporal and spatial resolutions are lower than with EMIC or full climate models. However, models that can provide high-resolution results need to be used to make the evaluations more precise. For the second point, climate change adaptation, which can reduce impacts, is also a key issue when considering an impact such as climate-change-induced labor productivity change. Analysis in such areas, however, was not possible in this study because additional models and/or data are required.

Future tasks remain for improving analysis of climate change's impacts on socioeconomic activities, including overcoming the abovementioned limitations. First, this study did not analyze the effect of climate change adaptation, which is as critical as mitigation, particularly in high-emission scenarios. To address labor productivity changes induced by climate change, adjusting worktimes and cooling workspaces are potentially effective measures. For example, daylight saving time in the hot season can be effective

toward shifting worktimes to cooler hours. There are still many regions in which to introduce this approach because it is mainly used only in North America and Europe. Even without daylight saving time, earlier work starting times can achieve the same effect (Takakura et al., 2017). However, shifting worktimes would not be as effective as an adaptation measure (Takakura et al., 2018); therefore, workplace cooling is also needed. Introducing air conditioning equipment is an effective measure for decreasing temperatures for indoor workers, particularly in the high-temperature developing economies, where there is less diffusion of such equipment than in developed economies. This can, however, increase energy demand (Waite et al., 2017). In addition to these measures, automation will be effective for reducing workplace heat stress. Given these considerations, assessing the cost of mitigation, impact, and adaptation simultaneously is clearly valuable.

Additionally, for integrating socioeconomic and climate models, more detailed climate models (e.g., EMIC and Earth system model) are needed for conducting in-depth assessment of the impact of climate change on socioeconomic conditions, as in some previous studies (Collins et al., 2015; Mercure et al., 2018; Monier et al., 2018; Paltsev et al., 2015; Thornton et al., 2017). These detailed models have particular advantages in time and spatial resolutions. This also relates to the first point, such as in evaluating the effect of adjusting worktimes.

Finally, there is importance in comprehensively evaluating various types of socioeconomic impact caused by climate change. Examples here include decreased land area, agricultural productivity changes, and influence on human health, as mentioned in section 1. While the economic impact of the labor productivity changes evaluated in this study was not large, considering a range of different impacts can show considerable effects. Comprehensive assessments of climate change impact, mitigation, and adaptation are therefore urgent measures for further understanding climate-change-related issues and their consequences toward combatting climate change and achieving a sustainable society.

Acknowledgements

This research was supported by the Integrated Research Program for Advancing Climate Models (TOUGOU program) of the Ministry of Education, Culture, Sports, Science and Technology of Japan, and JSPS KAKENHI grant numbers 18K11754 and 18K11800. The author thanks Adam Goulston from Edanz Group (www.edanzediting.com/ac) for editing a draft of this manuscript.

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